Migration, Labor Tasks and Production Structure in Europe*

Stefania Borelli[†] Giuseppe De Arcangelis[‡] Majlinda Joxhe[§]

This version: May 2017

Abstract

This paper assesses the effect of the immigration on the production structure in a selection of European countries in 2001-2009 with a task-based approach. The inflow of immigrants represents an increase in the relative supply of manual-physical (or simple) tasks, hence favoring simple-task intensive sectors. We use a new OECD dataset, PIAAC, to calculate the index of simple-task intensity at the country-industry level. The analysis confirms that the increase in migration stocks caused a positive impact on the value added of sectors that use more intensively simple tasks. These effects are more intense when considering countries as Italy and Spain characterized by a recent, rapid and intense inflow of migrants. Endogeneity issues are discussed and instruments based on a gravity approach are used in estimation.

Keywords: Rybczynski Effect, International Migration, PIAAC, Gravity Equation.

JEL Classification Codes: F22, C25.

---

*We are particularly grateful to Giovanni Peri and Paolo Naticchioni for their useful comments. We also want to thank all the participants at the International Economics Reading Group in Sapienza, at the Macroeconomic Seminar in the Department of Economics (Uppsala University) for their suggestions. Usual disclaimer applies.

[†]Department of Economics and Social Sciences, Sapienza University of Rome. Email address: stefania.borelli@uniroma1.it

[‡]Department of Economics and Social Sciences, Sapienza University of Rome. Email address: giuseppe.dearcangelis@uniroma1.it

[§]CREA-University of Luxembourg, Email address: majlinda.joxhe@uni.lu

Contents

1 Introduction and Literature Review **3**

2 Data and Descriptive Statistics on Migration **9**
2.1 A Useful Dataset for Task Variables: PIAAC 10

3 Empirical specification **25**

4 Endogeneity Problems and Econometric Strategy **27**

5 Estimation Results **37**
5.1 Evidence on Rapid-Immigration Countries 40

6 Concluding Remarks **54**

A An example of how using PIAAC to determine industry task intensities **59**
A.1 Case 1: no industry variation in terms of task intensities 59
A.2 Case 2: industry variation in terms of task intensities 61

B Activity Sectors NACE Under Different Revisions 1.1 and 2.0 **63**

1 Introduction and Literature Review

The incidence of foreign-born population on natives in European countries has greatly increased in the last three decades. According to United Nations (2015), the stock of foreign-born population in France, Germany, Italy and UK was 16.9 million in 1990 and reached 34.1 million in 2015. Along this increasing trend the dynamics has been different among the various countries. In Germany and France the foreign-born population respectively doubled and increased by slightly more than 30 per cent, whereas in Italy and Spain the 2015 foreign-born population stocks were respectively more than 4 and 7 times the stock in 1990. Different policy decisions has been taken, from amnesties in countries with rapid growth rates to tighter conditions to partecipate to the domestic labor markets.

In North America migration has been a continuous phenomenon and economists have been discussing the effect of immigration on the labor market for long time. Most studies focused on the impact of foreign-born workers on natives' wages and employment mainly in the low-skilled segment of the labor market. Borjas (2003) and Borjas and Katz (2007) argue that immigration reduced real wages paid to native-born workers without a high school degree. Card (2009), in contrast, find no effect of immigration on the wages of less-educated native workers. Ottaviano and Peri (2012) find a positive effect due to complementarity between natives and migrants. Peri (2016) and Dustmann et al. (2016) discuss the empirical characteristics of these studies and summarize the main results.

Regarding effects on the production structure, Hanson and Slaughter (2002) considered the local effect of the inflow of migrants in the US, whereas Gandal et al. (2004) analyzed the effects of the inflow of foreign workers in Israel, in particular from the former Soviet Union. Although in the former study the new labor force is typically low-skilled and in the latter one is typically high-skilled, both studies conclude for a more evident role of the changes in production techniques rather than changes in the production mix. Along the same line, Lewis (2004) analyzed the large inflow of Cuban migrants in Miami and reached similar conclusions on the rate of technology adoption rather than an effect in the industry mix. Card and Lewis (2007) and Card (2007) find effects on the production structure, but claim that this occurs within sectors (or within firms) rather than between sectors. Bettin et al. (2012) find evidence of production recomposition in favor of low-skilled manufacturing when using firm-level data for the case of Italy, but only for the years 2001-2003.

Looking at the type of change in production techniques, Accetturo et al. (2012) conclude for an increase in the capital-to-labor ratio when using Italian manufacturing data at the firm level, whereas Lewis (2011) finds a tendency to slow the adoption of automated techniques in US metropolitan areas where migration has been more intense.

In Europe economists have investigated the effect of immigrants in some countries using a similar approach. For instance, Dustmann and Glitz (2015) analyze the case of Germany and emphasize the role of newly created firms, whereas Gonzalez and Ortega (2011) and De Arcangelis et al. (2015) present studies respectively for Spain and Italy.

Among the many studies on European countries we recall D'Amuri and Peri (2014) where they underline the positive effect on native workers who may upgrade to occupations where communication tasks involving an excellent knowledge of the domestic language and culture are necessary and leave manual-task intensive occupations to migrants. Wages do not change much, maybe due to much less flexible labor markets in Europe with respect to the US. Although small and limitedly significant, the effect on natives' wage is never negative.

When wages are not or just limitedly affected even in the short run, as it is the case for Europe, the literature has considered two possible effects. The increase in employment, associated with immigration, can lead to either (i) a change in the production mix in favor to sectors that use more intensively the type of employment that come with immigration, or (ii) a change towards production techniques that are more complementary to the characteristics of the new labor force.

Gonzalez and Ortega (2011) analyzed the inflow of migrants in Spain and found that the inflow of unskilled migrant workers into a region is almost completely absorbed through an increase in the intensity of use of unskilled labor, given the output mix. De Arcangelis et al. (2015) studied the Italian case and obtain a tendency towards output recomposition in favor of the simple-tax intensive manufacturing sectors at the province level.

This paper investigates the effect of immigration on the production structure in a selection of European countries with a *task-based approach*. Many recent studies have used the task-based approach to explore the causes of job polarization and the link between technological change and the shift in wage structure. In this strand of work there are Autor and Handel (2009), Goos and Manning (2003), GOOS et al. (2011), and many others. In these studies the primary hypothesis is that workplace computerization leads to the displacement of human labor in tasks that can be described as routine.

This approach has recently been applied also to study the effects of immigration. Peri and Sparber (2009), Ottaviano and Peri (2012), D'Amuri and Peri (2014) compare the task assignment of native and migrant workers with similar education.

In line with this latter task-based approach, the hypothesis at the origin of this work is that the inflow of migrants represents a positive shock that shifts the relative supply of manual-physical tasks with respect to complex-types of tasks. By assuming that the (relative) wages are constant, as observed for the European case, we estimate the effect of immigration on the production structure as sectoral recomposition: the increase in the (relative) supply of *simple* tasks is mainly absorbed by an increase in the weight of sectors characterized by higher simple-task intensity.

One of the main contributions of our work is the use of a new database, PIAAC (Programme for the International Assessment of Adult Competencies, OECD), to calculate the "Task Intensity Index" at industry level. Only three countries have task data available: the United States (see Autor et al. (2003)), Germany (see Spitz-Oener, 2006), and Britain (see Felstead et al., 2007). To the best of our knowledge, as reported in Table 1, the data sources for analysis on job tasks come from a module of the Princeton Data Improvement Initiative survey (PDII) to the Survey of Skills, Technology, and Management Practices (STAMP).

All datasets provide information on job tasks at the single-country level. The Princeton Data Improvement Initiative survey collects data on the cognitive, interpersonal, and physical job tasks that workers regularly perform on their jobs. The US Department of Labor's Occupational Information Network, which contains occupation-level measures and replaces the Dictionary of Occupational Titles as an official career counseling tool, is probably the dataset used more frequently in empirical works on jobs task. The survey of Skills, Technology, and Management Practices (STAMP) fielded by Michael Handel provides a detailed cross-sectional view of work activities in the U.S. German Qualification and Career Survey, which

Table 1: Data sources on job tasks

Dataset	Level	Country	Year	Works
Princeton Data Improvement Initiative survey (**PDII**)	Workers	USA	2008	Autor and Handel 2013
IAB/BIBB labor force data	Workers	Germany	1979, 1984/85, 1991/92, 1998/99, 2005/06	Spitz-Oener 2006
O*NET	Occupations	USA	Last version 2009	Autor et al. 2003
British Skills Survey **BSS**	Workers	UK	1986, 1992, 1997, 2001, 2006	Rojas and Romagosa 2013
Skills, Technology, and Management Practices (**STAMP**)	Workers	USA	2007	Handel 2007

is conducted jointly by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB) offer detailed self-reported data on workers' primary activities at their jobs. British Skills Survey (BSS) by Francis Green and collaborators, has sought to provide consistent measures of skills used in the workplace by surveying workers about their work activities. Both latter surveys are collected in different years, but data from BSS are comparable only for three years: 1997, 2001 and 2006. In IAB/BIBB, the set of job activity questions varies substantially across the different survey years. This almost certainly reduces the reliability of the IAB/BIBB data as a source for tracking the evolution of job-task inputs in aggregate.

The main advantage of using the international survey PIAAC, which also uses a self-reported individual worker's survey, is that it allows to highlight the country-specific differences across the European countries. Borelli (2016) provides a detailed comparison between the widely-used US dataset O*NET and PIAAC.

In this work the empirical specification isolates the effect of the inflow of foreign-born workers on the relative value added of the industries for the main European countries. Industries that use more intensively simple tasks should increase their relative weight in each country and the relative task intensity should originate also nonlinear effects magnifying the effect of the increased supply in simple tasks.

The typical problem of reverse causality may arise and we use various instrumental variables. Our instruments for the migration inflows are obtained by predicting industry's share of immigrant workers. In particular, we propose five different instruments: for the first four we use a two-step approach consisting in the estimation of the rate of growth of immigrants through a *gravity-based model*, similarly to Ortega and Peri (2014), and the subsequent imputation of the workers into industries following the shift-share approach initially proposed by Altonji and Card (1991) and Card (2001). The latter instrument is constructed by using the typical Altonji-Card approach at the geographical level without any gravity adjustment.

Our empirical findings confirm that, by raising the relative supply of the *simple* tasks, immigration affects positively the weight of the value added of the *simple*-task intensive sectors relatively to all other sectors.

The remaining sections of the paper are organized as follows. Section 2 describes the data and presents descriptive statistics of the immigration in the considered countries. Section 3 and 4 present respectively the empirical specification and econometric strategy, whereas 5 shows the empirical results considering respectively the full sample of countries and the two countries where *occupational segregation* is more pronounced. Section 6 concludes.

2 Data and Descriptive Statistics on Migration

In order to analyse the relationship between migration and production structure in the selected countries we use different data sources.

First, we use data from the European Union Labor Force Survey (EU-LFS) to obtain a multi-country comparable measure of employment for foreign-born workers.[1] In particular, we obtain the immigrants' distribution across countries of destination and industry (NACE Rev. 1.1 and Rev. 2). The analysis is restricted to 2001-2009 for the following countries: Belgium, Denmark, France, Netherlands, Norway, Spain, Sweden, United Kingdom, Germany (2002-2009) and Italy (2005-2009). Secondly, data on value added at the industry level (ISIC rev. 3) are obtained from the

[1] In line with the previous literature, immigrants are all foreign-born workers who were not citizens at birth. Working age population is as usuale defined as aged 15-64.

OECD Structural Analysis (STAN) Database. Between 2001 and 2009 the share of foreign born in total labor force has increased by nearly 50% reaching almost 12% in 2009 (Figure 1). Figure 2 reports the immigrant share in each one of the ten countries of interest in the same period. Different patterns appear in the data. In France the immigrant share has been relatively stable since the 1970s. Germany has experienced sustained growth in its foreign-born population over the last half century and in the Netherlands restrictive immigration policy has led to a decline of immigrant flows. All the other countries have experienced large increases over the last two decades, with particularly fast growth in Italy and Spain since the year 2000. Unlike Germany and France, for most of the last century Italy has been one of the most important emigration countries in Europe, but since the year 2000, it has experienced rapid growth in its foreign population, reaching 5.5 million individuals (about 10 percent of the population) by 2009. The migration experience of Spain resembles that of Italy. Since the end of the 1990s, Spain has been experiencing inflows of migrants at a rate surpassing that of any other European country. By less than 10 years the foreign-born share in Spain increased to 15.3 percent. Figure 3 reports the evolution of the employment shares of immigrant workers across sectors in each year when considering all countries together. The highest shares of foreign workers are particularly pronounced in sectors such as manufacturing, construction and low-skill service sectors with notable differences among countries.

2.1 A Useful Dataset for Task Variables: PIAAC

At last, the tasks performed by workers are constructed by using data from the Programme for the International Assessment of Adult Competencies (PIAAC). Quoting the OECD (2013): “The Survey of Adult Skills (PIAAC) assesses the proficiency of

Figure 1: Foreign born workers as share of total in EU 2001-2010

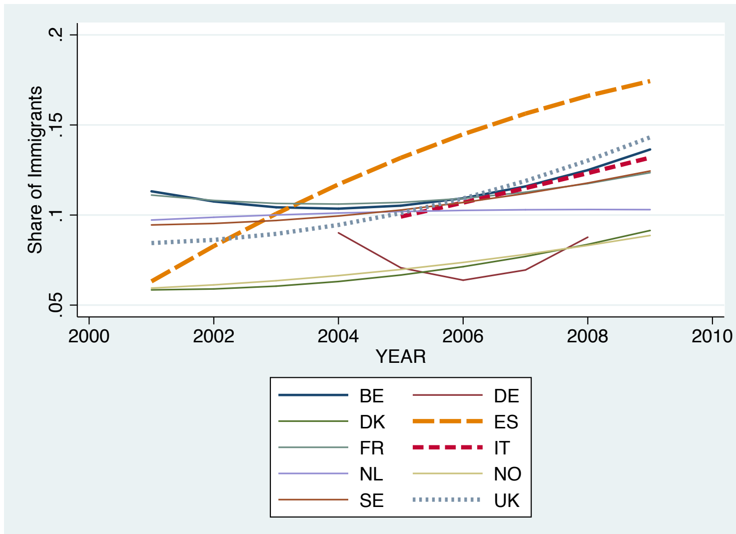
Source: Author's calculation from EU-LFS data.
It does not include countries for which one or more years of data are missing (Italy and Germany).

adults from age 16 onwards in literacy, numeracy and problem solving in technology-rich environments. These skills are "key information-processing competencies" that are relevant to adults in many social contexts and work situations, and necessary for fully integrating and participating in the labor market, education and training, and social and civic life. In addition, the survey collects a range of information on the reading- and numeracy-related activities of respondents, the use of information and communication technologies at work and in everyday life, and on a range of generic skills, such as collaborating with others and organising one's time, required of individuals in their work".

There are 24 national participants in PIAAC, comprising 20 OECD member countries, regional entities from two OECD member countries (UK and Belgium) and two partner countries (Cyprus and the Russian Federation).[2] Units of analysis

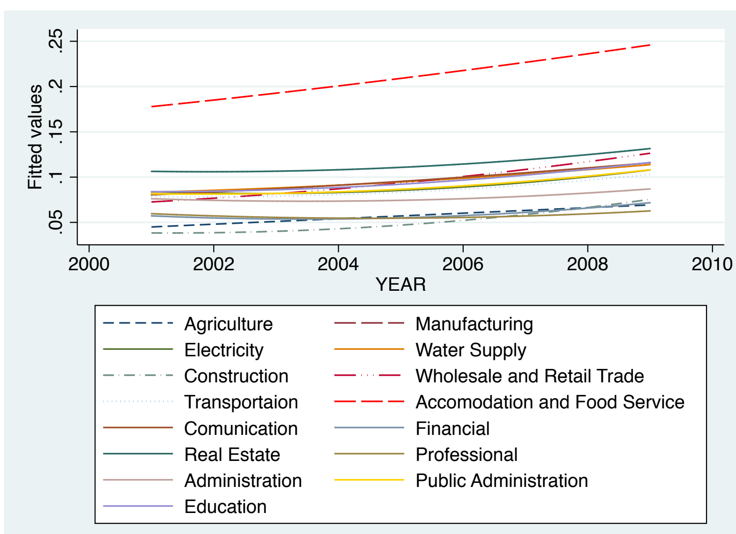
[2]Australia, Italy, Austria, Japan, Canada, Republic of Korea, Norway, Cyprus, Poland, Czech

Figure 2: Foreign born workers as share of total in EU 2001-2010, by country



Source: Author's calculation from EU-LFS data.

Figure 3: Foreign born workers as share of total in EU 2001-2010 across sectors



Source: Author's calculation from EU-LFS data.
It does not include countries for which one or more years of data are missing (Italy and Germany).

are the individuals and their competencies. The PIAAC target population consist of all adults, age 16 and 65, who resided in the country ("usual place of residence") at the time of data collection. Adults were to be included regardless of citizenship, nationality or language. The normal territorial unit covered by the survey was that of the country as a whole. The sampling frames used by participating countries are of three types: population registers (administrative lists of residents maintained at either national or regional level); master samples (lists of dwelling units or primary sampling units maintained at national level for official surveys); or area frames (a frame of geographic clusters formed by combining adjacent geographic areas, respecting their population sizes and taking into consideration travel distances for interviewers). The minimum sample size required for the Survey of Adult Skills depends on the number of cognitive domains assessed and the number of languages in which the assessment was administered. Assuming the assessment was administered in only one language, the minimum sample size required was 5000 completed cases if all three domains were assessed and 4500 if only literacy and numeracy were assessed.

In addition to the conventional measures of occupation and educational qualifications, PIAAC includes detailed questions about the frequency with which respondents perform specific tasks in their jobs. Indeed, PIAAC collected a considerable amount of information on the skills possessed and used by adults in addition to the measures of proficiency in literacy, numeracy and PSTRE. Based on this information, the survey gauges the usage of a wide range of skills, including both

Republic, Russian Federation, Denmark, Slovak Republic, Estonia, Spain, Finland, Sweden, Flanders (Belgium), United Kingdom, France, England (UK), Germany, N. Ireland (UK), United States of America. Although the Russian Federation participated in PIAAC, its data were not ready for inclusion in the first international report on PIAAC. The tables for England and Northern Ireland are available separately.

information-processing skills – which are also measured in the direct assessment – and generic skills, for which only self-reported use at work is available.[3]

The survey generated many items describing generic activities involved in each occupation. The choice of items is suggested by theories and practices of commercial psychology. To reduce the multiple items to a smaller and more meaningful set of 'generic tasks', statistical techniques[4] have been used in the project to generate several indicators from the responses.

In particular, twelve indicators were created, five of which refer to information-processing skills (reading, writing, numeracy, ICT skills and problem solving); the remaining seven correspond to general tasks (task discretion, learning at work, influencing skills, co-operative skills, self-organising skills, gross physical skills and dexterity).[5]

Borelli (2016) provides a detailed comparison between the widely-used US dataset O*NET and PIAAC.

[3]Quoting again OECD (2013):"Although there is some parallel between the skills included in the direct assessment exercise – literacy, numeracy and problem solving in technology-rich environments – and the use of reading, numeracy, problem solving and ICT at work (and at home), there are important differences. The skills use variables are derived by aggregating background questions on tasks carried out at work (or at home). For instance, these questions cover both reading and writing at work but two separate indices are created to maintain, to the extent possible, consistency with the direct assessment module which only tests reading skills in the literacy module. Similarly, the use of problem solving and ICT skills at work are not to be confused with the assessment of proficiency in problem solving in technology-rich environments. Finally, it should be kept in mind that even when there is a parallel between skills use and skills proficiency concepts – notably between reading use and literacy proficiency and between numeracy use and proficiency – there is no correspondence between the questions concerning the tasks performed at work (or at home) and those asked in the direct assessment modules. These issues should be kept in mind when comparing skills proficiency to skills use"

[4]For further information on the statistical techniques: Technical Report of the Survey of Adult Skills (PIAAC), Chapter 17: Scaling PIAAC Cognitive Data.

[5]For these skills-use variables numerical comparisons between the use of different skills are possible: a value of 0 indicates that the skill is never used; a value of 1 indicates that it is used less than once a month; a value of 2 indicates that it is used less than once a week but at least once a month; a value of 3 indicates that it is used at least once a week but not every day; and a value of 4 indicates that it is used every day.

Following how Peri and Sparber (2009) combined US occupational data with O*NET information, similarly we merge the information contained in PIAAC with data on the European Labor Force Survey.

In particular, we weigh the task-specific values (score between 0 and 4) from PIAAC for each occupation with the number of European workers in each occupation in 2000 according to the European Labor Force Survey, country by country. As a result, we are able to obtain a scale whose values equal the percentile score of that task in that year with a standardized measure of the relative importance of each task among European workers. Then, for instance, a task with a score 0.06 in France indicates that only 6 percent of workers in France in 2000 were supplying that task less intensively.

We consider a partition of productive tasks into "complex" tasks (cognitive, interactive and organising/problem-solving tasks) and "simple" tasks (manual tasks) and then we construct an index for each group of tasks as the mean of the scores. The main addition with PIAAC is that we can have an industry variation that is absent in the US-based O*NET. Each index is constructed as a mean of the competency scores, where the competencies/variables for each index are given in Table 2.

In the Appendix A we give a very simple example of how the PIAAC scores have been combined with the Labor Force Survey data in order to recover the measure of each task importance. Moreover, we highlight the main addition of industry variation that PIAAC offers with respect to O*NET, but also the drawback of such measures when they are not used in relative terms.

Indeed, we have computed a synthetic *Simplicity Index* summarizing the intensity of manual skills relative to cognitive-organising-interactive skills and this is defined as follows:

Table 2: **Task Types and Variables from PIAAC**

Type of skill	**Sub-type of skill**	**PIAAC Variables**
Manual Skills	Dexterity	Using hands or fingers
	Finger Dexterity	
	Physical Activities	Working physically for long
Cognitive Skills	Writing	Index of use of writing skills
	Reading	Index of use of reading skills
	Mathematics	Index of use of numeracy skills
	Use of PC	Index of use of ICT skills
	Learning Activities	Index of readiness to learn
Organising and Problem Solving Skills	Problem Solving	Complex Problems
	Planning	Planning Own Activities
		Planning Others Activities
		Organizing Own Time
Interactive Skills	Selling	Selling
	Teaching	Teaching People
	Consulting	Advising People
	Persuading	Influencing People
	Communicating	Presentations
	Negotiating	Negotiating with People
	Planning	Planning Others Activities
	Cooperation	Sharing Work-related Info

Source: Authors' elaboration from PIAAC data.

$$S_s = ln\left[\frac{MII_s}{CII_s + III_s + OII_s}\right]$$

where s is referred industry , MII_s, III_s, OII_s and CII_s are respectively the Manual Intensity Index, the Interactive Intensity Index, the Organising and Problem Solving Index and the Cognitive Intensity Index. The index S_s has been normalized between 0 and 1 (the industry with the highest Simplicity Index has score 1 and the industry with the lowest Simplicity Index has score 0).

Figures 4, 5 and 6 plot the share of foreign workers in 2001-2009 relative to total workers (foreign + native) in each sector against, respectively, the Manual Intensity Index, Cognitive Intensity Index, Interactive Intensity Index, Organising-Problem Solving Intensity Index and Simplicity Index. Each point in the graph represents the immigrant workers' share in a specific sector and the line represents the relative interpolation.

Looking at the graphs, it is clear that that immigrants are proportionately more represented in sectors characterized high Manual Intensity Index. The relation between share of foreign workers and the indices becomes negative when the Cognitive Intensity Index, the Interactive Intensity Index, the Organising-Problem Solving Intensity Index are considered. The relationship between the share of foreign workers and the Simplicity Index is positive.[6] These results confirm what previous research has found for the US. In particular, Ottaviano et al. (2013) reports similar findings using US Data and O*NET breakdown.

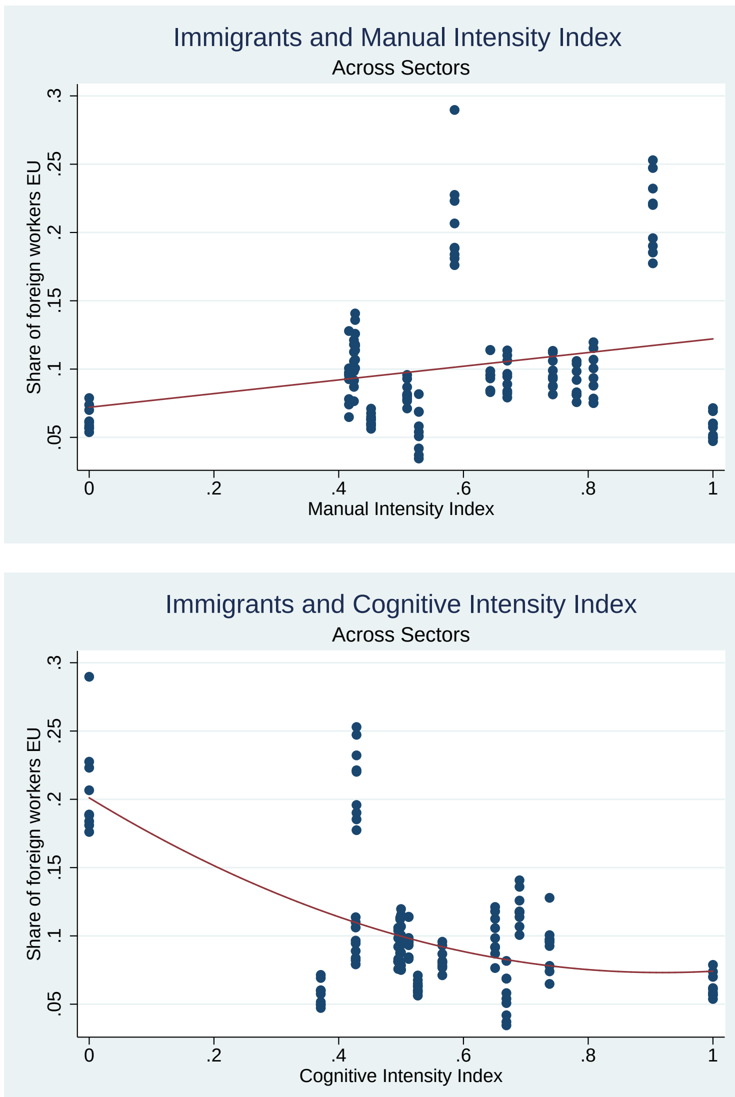
In Figures 7, 8 and 9 we report the same graphs as above but for ten countries: the positive relation between the share of foreign workers and Manual Intensity Index

[6]Graphs in figures 4 and 5 are constructed using the total share in all considered countries as a share of immigrant workers and the mean of the each index in all countries as Intensity Index.

is clearly positive for some countries as Belgium, Germany, Spain, France, Italy and Sweden, but less evident for Denmark, Netherlands, Norway and UK. Looking at the summarizing Simplicity Index, the positive relationship with the share of foreign born workers is stronger for some countries than in others.

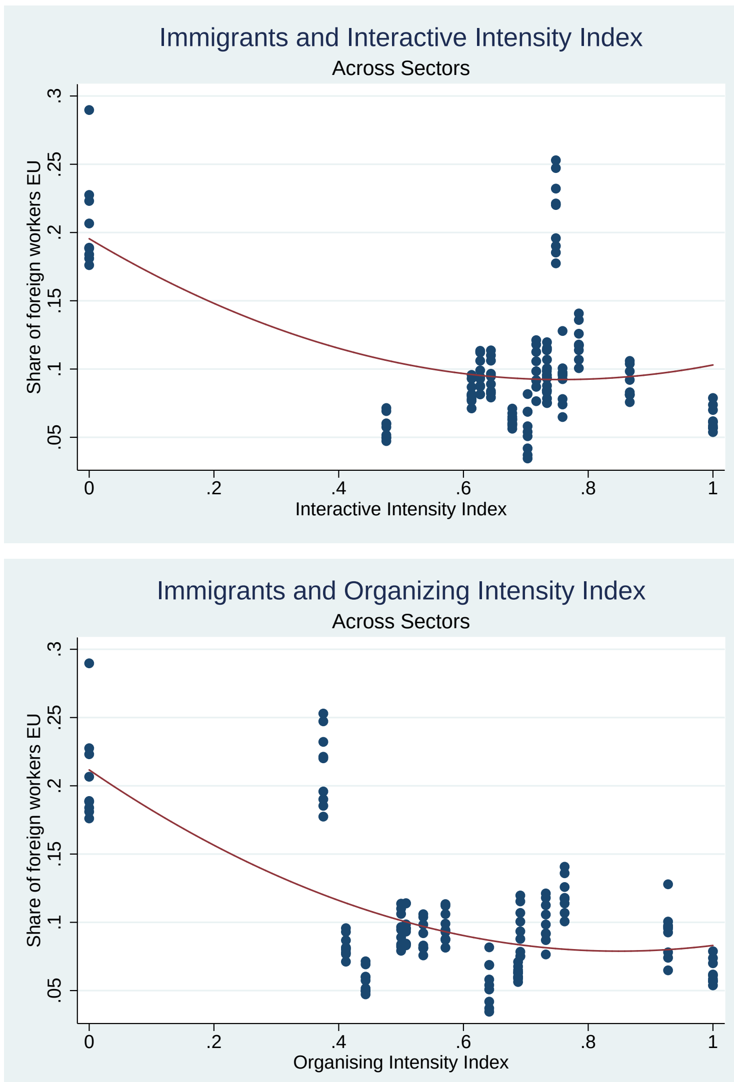
The final conclusion is that immigrants are proportionately more represented in sectors characterized by a high Simplicity Index, but the relationship between the share of immigrant workers and the Simplicity Index appears to be country-specific, hence justifying even more convincingly the use of a country-specific dataset as PIAAC rather than the one-size-fits-all O*NET.

Figure 4: Immigrant Workers and Manual or Cognitive Intensity Indices, across Sectors



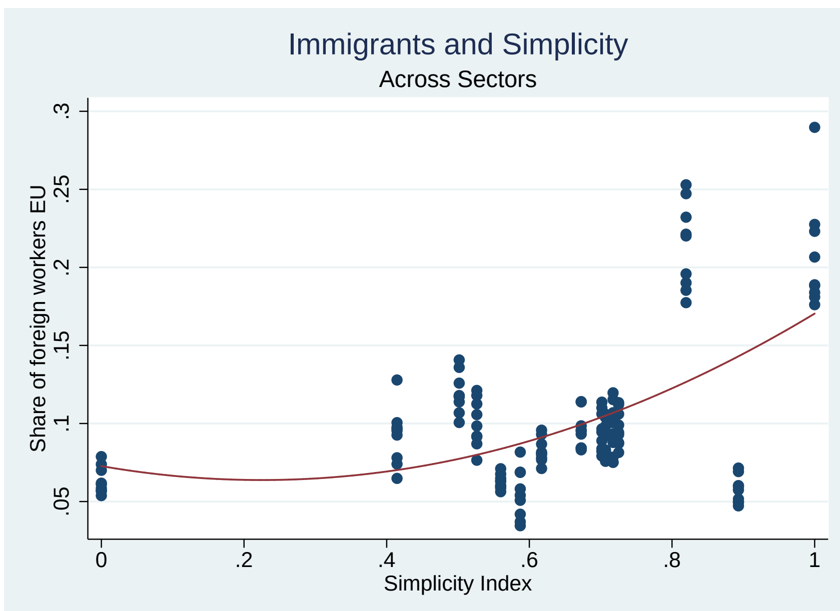
Source: Elaboration of data PIAAC and EU-LFS (Selected Countries)

Figure 5: Immigrant Workers and Interactive - Organising Intensity Indices, across sectors



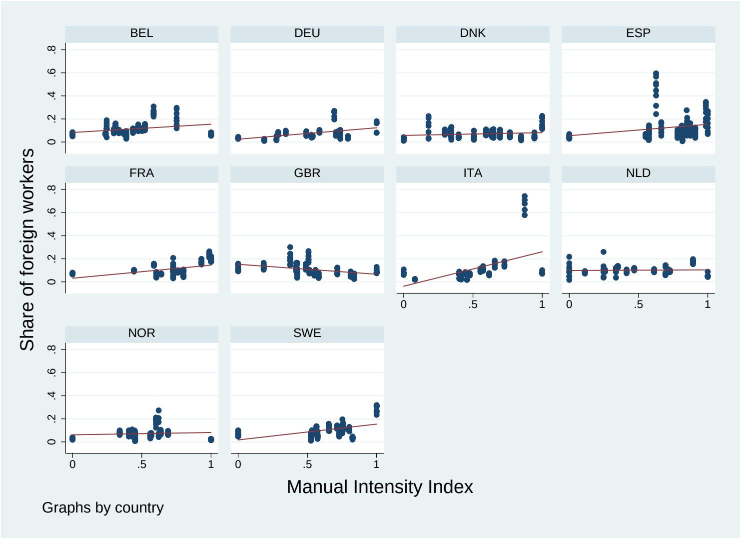
Source: Elaboration of data PIAAC and EU-LFS (Selected Countries)

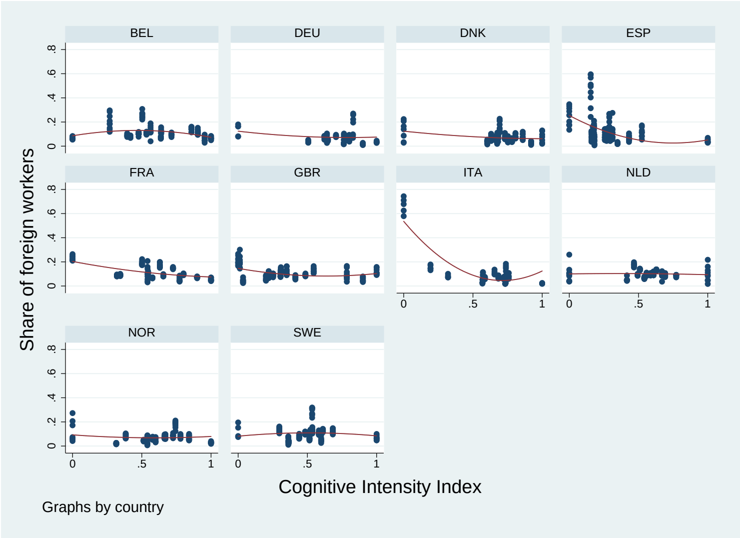
Figure 6: Immigrant Workers and Simplicity Index, across Sectors



Source: Elaboration of data PIAAC and EU-LFS (Selected Countries)

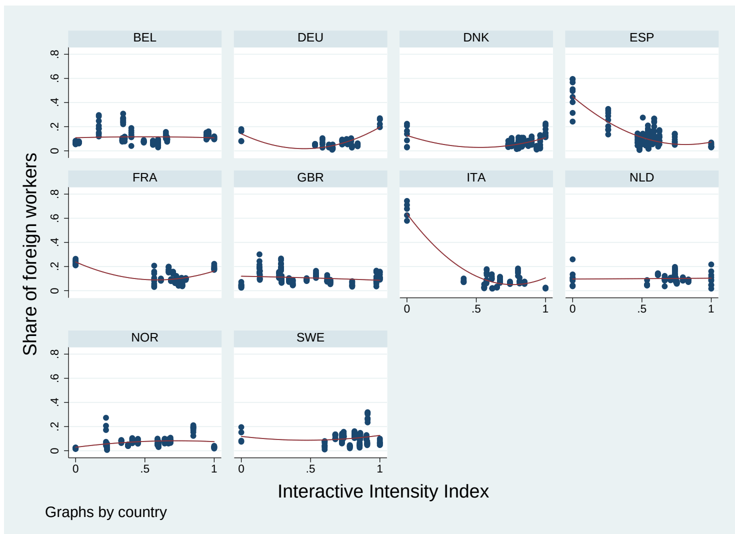
Figure 7: Immigrant Workers and Manual - Cognitive Intensity Indices across Sectors, by country

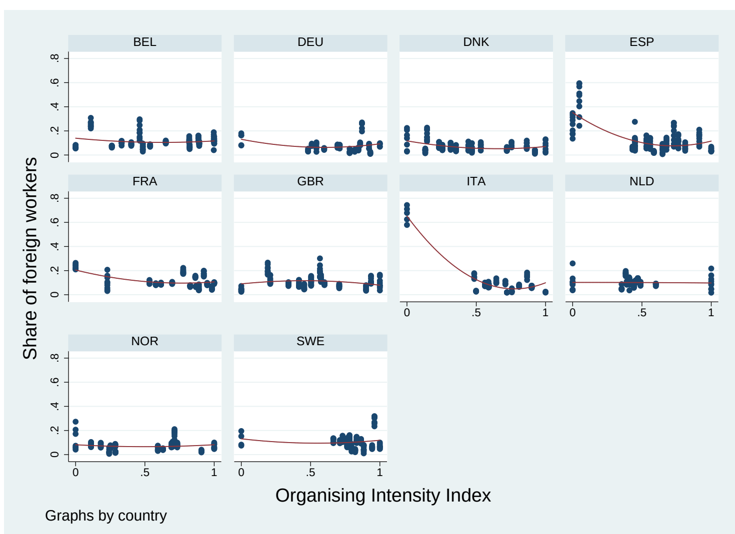




Source: Elaboration of data PIAAC and EU-LFS (Selected Countries)

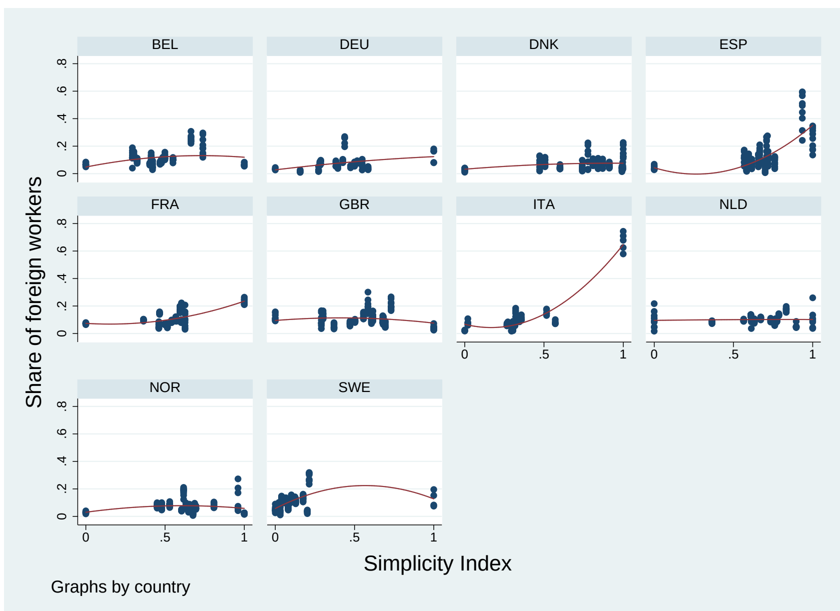
Figure 8: Immigrant Workers and Interactive - Organising Intensity Indices across sectors, by country





Source: Elaboration of data PIAAC and EU-LFS (Selected Countries)

Figure 9: Immigrant Workers and Simplicity Index across Sectors, by country



Source: Elaboration of data PIAAC and EU-LFS (Selected Countries)

3 Empirical specification

The aim of this work is to analyse the relationship between migration and the production structure of the European economies in 2001-2009. In particular, the main objective is to provide evidence of an increase (in terms of value added) of simple-task intensive sectors when the incidence of migrants on the total country population rises – what recalls a sort of Rybczynski effect.[7]

The analysis is conducted at the sector/country level, using data on migrants' employment from EU-LFS (2001-2009) and data on Value Added from OECD-STAN (2001-2009).

In particular, we estimate the relationship between the value added of sector s in country c at time t and the weight of foreign-born employment in the same sector, as measured by the ratio of the foreign-born workers to total employment. The sectors are detailed at the NACE (rev. 2) 1-digit level.

The sectors of each country's economy are ordered according to the Simplicity Index (as described in Section 2) in descending order from the *simplest* sector to the *most complex* one. According to the model, an inflow of migrants should be associated with an increase in the relative weight of the less complex-task intensive sector. A variation in the migrants-to-total workers population ratio is assumed as a reliable indicator for the changes in the composition of relative task supply, as also assumed in Peri and Sparber (2009), D'Amuri and Peri (2014) and De Arcangelis et al. (2015). The intensity of the effect on the value added should then be positively correlated with the *Simplicity* of the sector.

The model specification is as follows:

[7]For a theoretical presentation of this effect within the task approach in a framework similar to a factor-specific model see De Arcangelis et al. (2015), where it is provided empirical evidence but only for Italy.

$$\frac{VA_{sct}}{\sum_s VA_{sct}} = \beta_0 + \beta_1 \left(\frac{MIG}{POP}\right)_{sct} + \beta_2 S_{sc} + \\ + \beta_3 S_{sc} \left(\frac{MIG}{POP}\right)_{sct} + \text{country and time effects} + \epsilon_{sct} \tag{1}$$

where the dependent variable $\left(\frac{VA_{sct}}{\sum_s VA_{sct}}\right)$ is the weight of of sector s in terms of the value added *VA* with respect to the national, country c *VA* at time t. The covariate of interest is the ratio migrants-to-total workers in the sector s in country c at time t, $\frac{MIG}{POP}_{sct}$. This latter variable is also interacted with the index of *Simplicity* of sector s in country c, S_{sc}, by assuming a nonlinear effect. The hypothesis is that the share of foreign workers may have stronger effects in simple-task intensive sectors.

Accordingly, the marginal effect of immigrant workers on the value added can be denoted as:

$$\frac{\partial \frac{VA_{sct}}{\sum_s VA_{sct}}}{\partial \left(\frac{MIG}{POP}\right)_{sct}} = \beta_1 + \beta_3 S_{sc} \tag{2}$$

Two scenarios can occur. In one case the high level of the simplicity intensity has an accelerating effect and β_3 has the same sign as β_1. In the other case the high level of S_{sc} has a dampening effect and β_3 has the opposite sign of β_1.

Since $S_{sc}\left(\frac{MIG}{POP}\right)_{sct}$ is an interaction between two continuous variables, it is useful to subtract the total mean so that the mean of this new variable is zero, i.e. centering the variable. In this way multicollinearity is reduced and the regression results become more easily interpretable as β_3 is the marginal effect of the inflow of migrants when both variables are at the mean. The coefficient β_3 can also be re-estimated at different levels of variables, respectively at a *high* and a *low* level, i.e., one standard deviation above and one standard deviation below the mean.

Equation (1) is initially estimated by simple OLS under different specifications. The issue of reverse causality and endogeneity in the our covariate of interest is discussed in the following section.

4 Endogeneity Problems and Econometric Strategy

The estimates by OLS can be inconsistent and affected by the typical endogeneity bias: migrants' location choices are not random and the drivers for these choices (e.g. network effects, economic magnet effects) may be related to the sector performance, i.e. correlated with our dependent variable. Hence, we propose an Instrumental Variable (IV) method where the suggested instruments are inspired by the recent literature on migration. In particular, we elaborate five different instrumental variables: the first four are based on a gravity-model approach and the last one is based on the shift-share strategy first developed by Altonji and Card (1991).

The first instrument (named IV1 henceforth) is developed using a gravity approach similarly to Ortega and Peri (2014) by means of our data from European Labor Force Survey (EU-LFS) and variables obtained from the dataset cited in Ortega and Peri (2014) that includes information on migration flows and stock for 15 destination countries and 120 countries of origin for the period 1980-2006.[8] Since our estimation stretches to 2009, we added the missing data on migration flows from the International Migration Dataset (for France from IMD and CEPII) for the period 2007-2009. We name it as the OP-IMD dataset.

More precisely, we estimate country-pairs growth rates of migration that we

[8]These data can be downloaded in Stata format from Giovanni Peri's website.

aggregate at the level of larger country groups of origin.

The final country groups are: North Africa and Near Middle East, Other Africa, North America and Oceania, Central and South America, South and Eastern Asia, Other Europe, EU 15, New Members of EU. As in Ortega and Peri (2014) we build IV1 including only the determinants of bilateral migration flows that are exogenous to specific location decisions. The following bilateral variables are included: geographical area dimension and population of two countries, geographical distance, dummies for common border, common language and past colonial relationship. The gravity equation of migration flows from country j (belonging to the country group a) to country c takes the following specification:

$$\begin{aligned} ln\left(\frac{MIG}{POP}\right)_{c,j,t} &= \alpha_0 + \alpha_1 ln(POP)_{jt} + \alpha_2 ln(AREA)_j + \alpha_3 ln(POP)_{ct} + \\ &+ \alpha_4 ln(AREA)_c + \alpha_5 ln(DIST)_{jc} + \alpha_6 BORDER_{jc} + \\ &+ \alpha_7 LANGUAGE_j + \alpha_8 COLONY_j + \epsilon_{cjt} \end{aligned} \tag{3}$$

where $ln\left(\frac{MIG}{POP}\right)_{jct}$ is the share of migrants from origin country j in destination country c; $ln(POP)_{jt}$ and $ln(AREA)_j$ are the log of population and geographical dimension of country j (in Km^2) while $ln(POP)_{ct}$ and $ln(AREA)_c$ refer to country c; $ln(DIST)_{jc}$ is the log of distance between country j and country c (distance in Km between the capitals); $BORDER_{jc}$ is a dummy equal to one if country j and country c share a common border; $LANGUAGE_j$ is a dummy equal to one if in country j at least 9% of the population speaks the same official language of country c; $COLONY_j$ is equal to one if in the country j was a former colony of the destination country c.

Fitted values do not include the contribution of the fixed effects in explaining migration flows because they may not necessarily reflect the decision of migration. As expected, results show that geographic distance discourages migration flows, which conversely is favored by common borders, common language and past colonial relationship between home and partner country. Results are available upon request.

The gravity "instrument" is given by the OLS predicted bilateral migrant share in estimated Equation (3): $\left(\widehat{\frac{MIG}{POP}}\right)_{c,j,t} = exp\left(\widehat{\alpha}\mathbf{X}_{c,j,t}\right)$ where the vector $\mathbf{X}_{c,j,t}$ contains the whole set of regressors and the vector $\widehat{\alpha}$ contains the estimated coefficients in Equation (3). We collapse the coefficients by the country group of origin and we construct the overall growth rates of each area-of-origin immigrant group in each country of destination.

From EU-LFS data the first available information on the areas of origin of immigrants dates 2004 and we determine the initial 2004 distribution of foreign born workers as share of the total by area of origin, industry and country of destination.[9] The instrument is obtained by multiplying the initial distribution by area-of-origin of foreign born workers in each destination country by the growth rate of migrants determined from estimated Equation (3). Finally, we aggregate across areas of origin within each country, industry and year and obtain the total migration.

For the second instrument IV2 we estimate directly the gravity equation per area of origin rather than per single country of origin and then aggregate. The gravity equation to estimate is then as follows:

[9] For Italy this information is available from 2005

$$
\begin{aligned}
ln\left(\frac{MIG}{POP}\right)_{c,a,t} = \gamma_0 + \gamma_1 ln(POP)_{at} + \gamma_2 ln(AREA)_a + \gamma_3 ln(POP)_{ct} + \\
+\gamma_4 ln(AREA)_c + \gamma_5 ln(DIST)_{ac} + \gamma_6 BORDER_{ac} + \\
+\gamma_7 LANGUAGE_a + \gamma_8 COLONY_a + \epsilon_{c,a,t}
\end{aligned} \tag{4}
$$

where $ln\left(\frac{MIG}{POP}\right)_{act}$ is the share of migrants from area-of-origin a in country c; $ln(POP)_{at}$ and $ln(AREA)_a$ are the log of population and geographical dimension of area a while $ln(POP)_{ct}$ and $ln(AREA)_c$ refer to country c; $ln(DIST)_{ac}$ is the log of mean distance between area-of-origin a and country c (in Km); $BORDER_{ac}$ is a dummy equal to one if at least one country in area-of-origin a and country c share a common border; $LANGUAGE_a$ is a dummy equal to one if in at least on country in area-of-origin a at least 9% of the population speaks the same official language of country c; $COLONY_a$ is equal to one if in at least one country in the area-of-origin was a former colony of country c. In this case we directly obtain $\widehat{\left(\frac{MIG}{POP}\right)}_{c,a,t} = exp\,(\widehat{\gamma}\mathbf{X}_{c,a,t})$.

As with the first instrument, we construct the overall growth rates of each area-of-origin immigrant group and the instrument is obtained by multiplying the initial 2004 distribution (from EU-LFS data) of foreign born workers in each country of destination and industry and from various area-of-origin by the growth rate of migrants. Finally we aggregate across area of origin within each country, industry and year.

The third instrument IV3 is constructed using the same fitted values of IV1, but we can fully use the distribution by country of origin (without aggregating) since we can obtain the initial distribution of immigrant workers across sectors by country of origin from the Database on Immigrants in OECD countries (DIOC). Indeed, DIOC provides comprehensive and comparative information on a broad range of demographic and labor market characteristics of immigrants living in OECD countries. The main sources of data are population censuses and population registers, sometimes supplemented by labor force surveys. In particular, the DIOC includes information on place of birth and sectors of activity. The reference year is 2000; hence, by using DIOC data we can obtain the initial distribution of immigrant workers by country of origin and sector for the year 2000. The main disadvantage is that it does not cover all countries available with EU-LFS, but only Denmark, Spain, United Kingdom, Italy, Norway and Sweden.

We construct the overall growth rates of each country-of-origin immigrant group and the instrument is obtained by incrementing the initial distribution in each country of destination by the growth rates of foreign born workers coming from the different countries of origin. Finally, we aggregate across countries of origin within each country, industry and year.

In the IV4 we use the same fitted values of IV2 by areas of origin for the growth rates of immigrants and contruct the total number of migrants with the initial distribution in the year 2000 as obtained from DIOC.

The method used in IV4 implies that the variation in immigrant shares across industries and years is only driven by the initial composition of immigrants by area-of-origin and sector of activity (that now dates back to 2000) and the growth rates in the aggregate area-of-origin groups over time as estimated in Equation 4.

The last instrument, IV5, is based on the shift-share method proposed by Altonji and Card (1991) and Card (2001) and is developed using only information contained in EU-LFS dataset. In this case the initial immigrants' distribution across countries of destination and industry comes from the year 2000. This initial share is kept fixed and the number immigrants increases by the aggregate growth rate of the specific immigrant workers group in the European Union relative to the total workers. Then within an industry we obtain the imputed share of foreign-born in total employment.

As a consequence, the stock of immigrants imputed with this method depends on the initial distribution of immigrants across countries and industries, and on the evolution of the total number of foreign born in Europe.

Tables 3 and 4 report, respectively, the results of the gravity first-stage OLS equations for the two specifications. Table 3 reports the results using data from the OP-IMD and the resulting predicted values are used to construct the growth rate for IV1 and IV3. Table 4 reports the results using data from EU-LFS, where we consider migrants' macro-areas of origin and the resulting predicted values are used to construct the growth rates for IV2 and IV4.

Figures 10-12 shows the correlation between the instruments and the observed migrants-to-total ratio and it ensures relevance for the instruments.

Table 3: Gravity-based Instrument, data from OP-IMD

Dep. Var.: $ln(Mig)/(Pop)_{cj}$	
$ln(Pop)_c$	-.336***
	(.018)
$ln(Area)_c$	.098***
	(.019)
$ln(Area)_j$	-.051***
	(.012)
$ln(Pop)_j$	.851***
	(.015)
$ln(Dist)_{cj}$	-1.187***
	(.022)
$Border_{cj}$	-.358**
	(.132)
$Colony_{cj}$	1.292***
	(.094)
$Language_{cj}$	1.448***
	(.092)
R^2	.614
Observations	8211
FE	No

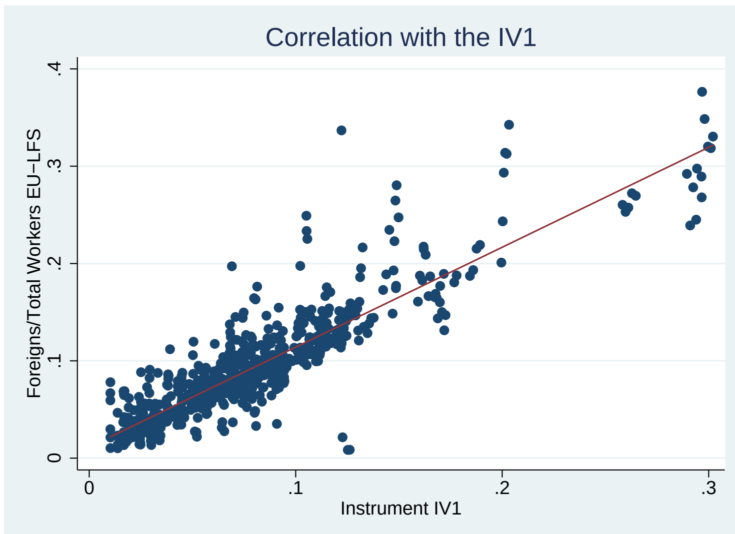
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the log of the ratio of bilateral migration from Country j to Country c to population in Country c at time t excluding zero values. Data for migration from OP-IMD.

Table 4: Gravity-based Instrument, data from EU-LFS

Dep. Var.: $ln(Mig)/(Pop)_{cj}$	
$ln(Pop)_c$	-.265***
	(.007)
$ln(Area)_c$	.145***
	(.007)
$ln(Area)_a$	.484***
	(.009)
$ln(Pop)_a$	.199***
	(.017)
$ln(Dist)_{ca}$	-1.119***
	(.023)
$Border_{ca}$	.113**
	(.040)
$Colony_{ca}$	.245***
	(.042)
$Language_{ca}$	1.102***
	(.017)
R^2	.530
Observations	10181
FE	No

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the log of the ratio of bilateral migration from Macro-area a to Country c to population in Country c at time t excluding zero values. Data for migration from EU-LFS.

Figure 10: Relationship between the Share of foreign born to Total Workers and Instruments IV1 and IV2



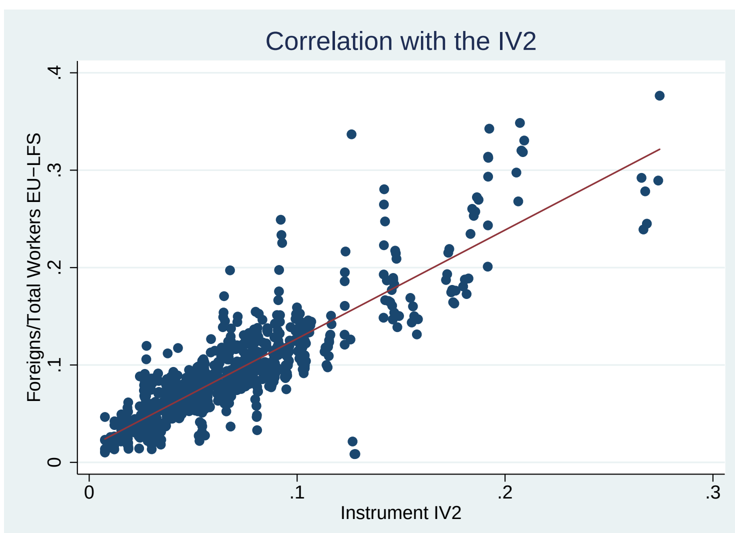


Figure 11: Relationship between the Share of foreign born to Total Workers and Instruments IV3 and IV4

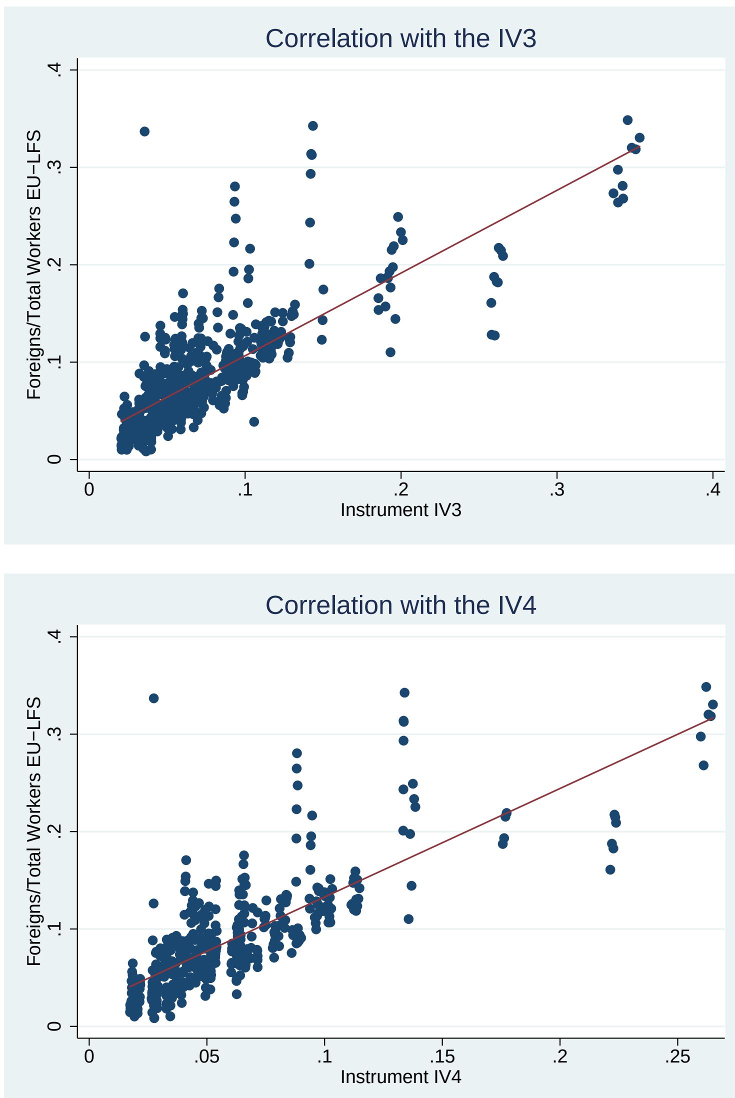
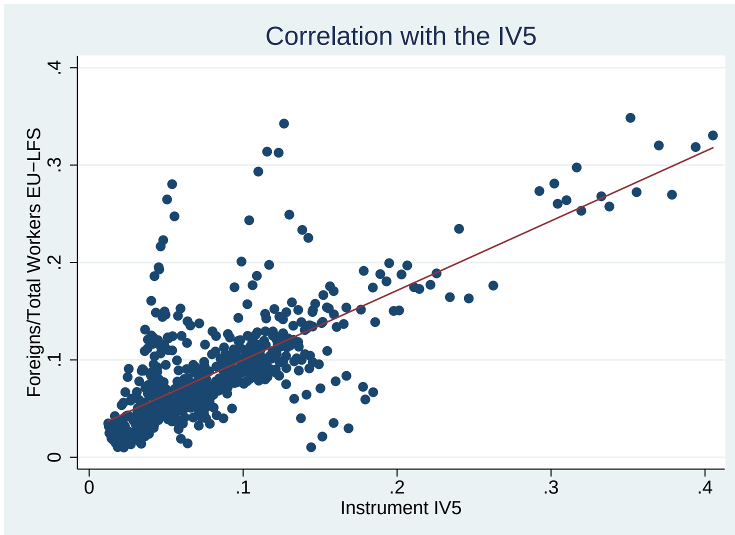


Figure 12: Relationship between the Share of foreign born to Total Workers and its Instrument IV5



5 Estimation Results

In Table 5 we report the OLS estimation results of the baseline regression, equation (1).[10] The first three columns refer to the specifications without time and country effects for the three cases regarding the different transformations of the covariates for a proper inclusion of the interaction term.

More specifically, the first column reports the results when the variables $\left(\frac{MIG}{POP}\right)_{sct}$ and S_{sc} are at their means. The second column refers to the specification in which the covariates of interest are at their means plus one standard deviation (s.e.) and the third column reports the results when the variables are at their means minus one standard deviation. The last three columns reports the results when time and country effects are included.

[10]Estimation results do not include the “Activities of household as employers” sector (where the employment share of foreign-born is particularly relevant) because the total weight in GDP is lower than 0.1 percent.

The estimated value of the direct marginal effect of migration – the coefficient β_1 in Equation (1) – is positive and significant only when locally estimating the effect around high values of $\left(\frac{MIG}{POP}\right)_{sct}$, i.e demeaned $\left(\frac{MIG}{POP}\right)_{sct}$ plus one s.e. meaning that the expected positive (Rybczynski) effect occurs only when the presence of migrants is high. The direct effect is still positive when the covariate is at the mean and significantly negative for low presence of migrants.

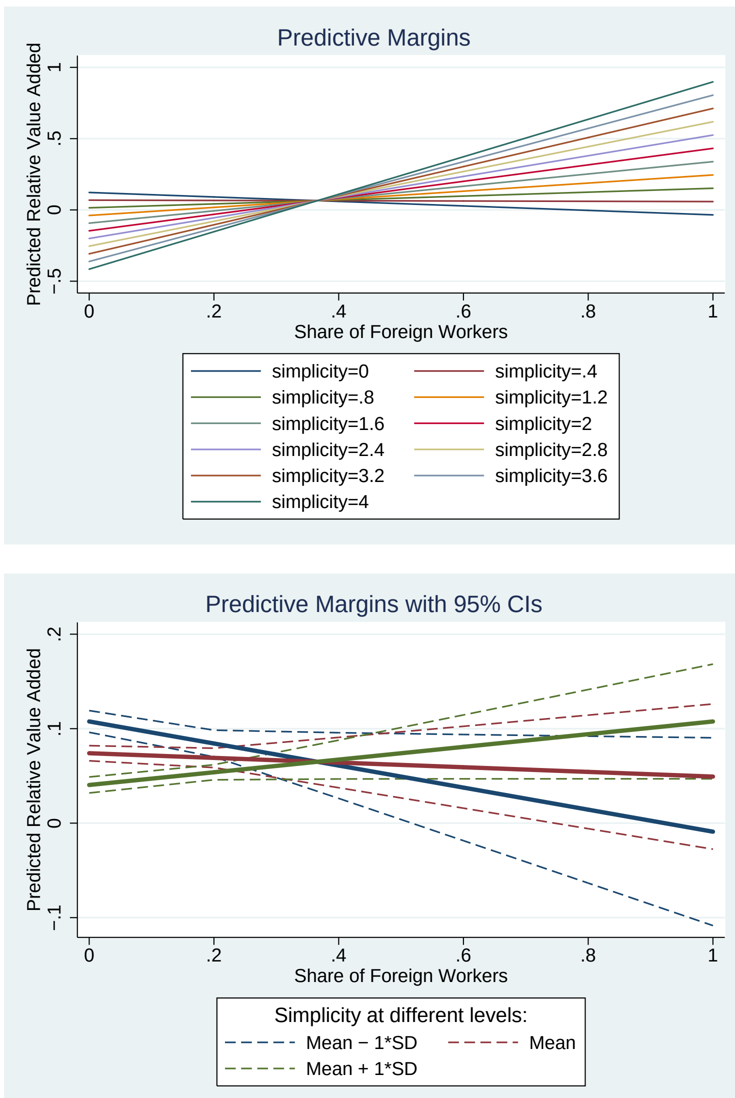
In line with the maintained hypothesis of this work, the coefficient β_3 is positive and significant in all specifications and it does change among the different specifications. We recall that a positive coefficient β_3 means that the nonlinear effect accelerates the positive effect of β_1 or dampens the negative effect of β_1. In all specifications (without and with country and time effects) the coefficients β_1 and β_3 are both positive when I consider the variables $\left(\frac{MIG}{POP}\right)_{sct}$ and S_{sc} at their mean plus one standard deviation.

Figure 13 illustrates how the marginal effects of the share of immigrant workers on the relative value added change over the range of the industry's simplicity. The graphs show that, as simplicity increases, the effect of the increase of immigrant workers on relative value added gets positive.

However, these results may be affected by the endogeneity of the migration rate. Hence, Tables 6–10 presents the results obtained by the IV-2SLS method with the instruments IV1-IV5 discussed in the previous section. In all regressions, the tests for underidentification (Kleibergen-Paap LM test) and weak identification (Kleibergen-Paap Wald test) reject the null hypothesis at the common significance levels. This confirms that the instruments are sufficiently correlated with variables of interest.

As in Table 5, the first three columns refer to the specifications without country and time effects that are instead included in the last three columns. The pattern of

Figure 13: Marginal effect of share of foreign workers on relative value added for different levels of the Simplicity Index



these results is more in line with our expectations since β_1 is no longer negatively significant even in the case on *low shares of foreign born workers*, whereas the coefficient β_3 is still positive and significant. Only when considering the IV5 instrument (Table 10), the results are not significant.

In conclusion, considering immigration as an increase in the relative supply in *simple* tasks with respect to *complex* tasks, our results seem to confirm an adjustment in the production mix with an additional, non-linear effect for the sectors that use more intensively *simple* tasks. In quantitative terms, doubling the presence of migrants in the domestic labor force on average increases the weight of simple-task intensive sectors by 0.2%.

5.1 Evidence on Rapid-Immigration Countries

Could the effect on value added be affected by the different historical trends of immigration in the destination countries? As mentioned in Section 2, immigrants, in general, are employed in simplest sectors (or occupations). Dustmann and Frattini (2011) provide comparative evidence on the occupational gaps for their sample of 15 EU countries and measure the degree of segregation of immigrants into particular occupations by means of an index of skills, the so-called ISEI scale, that they use to estimate the differences in the distribution of immigrants relative to natives along this scale. This occupational "segregation" is more pronounced in Italy and Spain than in other considered countries. A possible explanation of this phenomenon can be the recent, rapid and intense inflow of immigrants. Considering only Spain and Italy, Tables 11 – 16 report the results of the same regressions. As in Tables 5– 10 the first three columns refer to specification without country and time effects.

Table 5: Regression OLS

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.011			-.006		
	(.040)			(.041)		
S * Mig/Tot at Mean	.357***			.368***		
	(.067)			(.068)		
S at Mean	-.090***			-.100***		
	(.008)			(.009)		
Mig/Tot at Mean+1sd		.161***			.149***	
		(.031)			(.033)	
S * Mig/Tot at Mean+1sd		.357***			.368***	
		(.067)			(.068)	
S at Mean+1sd		-.067***			-.075***	
		(.009)			(.009)	
Mig/Tot at Mean-1sd			-.138*			-.160**
			(.062)			(.062)
S * Mig/Tot at Mean-1sd			.357***			.368***
			(.067)			(.068)
S at Mean-1sd			-.114***			-.124***
			(.010)			(.011)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.119	.119	.119	.122	.122	.122
Observations	1098	1098	1098	1098	1098	1098

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation *** p<0.01,** p<0.05, * p<0.1.
Considered countries: Belgium, Denmark, Spain, UK, Germany, Netherlands, Italy, France, Norway and Sweden.
Years: 2001-2009

Table 6: Regression IV1

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.068			.069		
	(.062)			(.063)		
S * Mig/Tot at Mean	.249*			.264*		
	(.106)			(.107)		
S at Mean	-.101***			-.112***		
	(.012)			(.014)		
Mig/Tot at Mean+1sd		.173***			.180***	
		(.050)			(.054)	
S * Mig/Tot at Mean+1sd		.249*			.264*	
		(.106)			(.107)	
S at Mean+1sd		-.084***			-.095***	
		(.012)			(.014)	
Mig/Tot at Mean-1sd			-.036			-.042
			(.096)			(.096)
S * Mig/Tot at Mean-1sd			.249*			.264*
			(.106)			(.107)
S at Mean-1sd			-.117***			-.130***
			(.015)			(.017)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.121	.121	.121	.125	.125	.125
Observations	643	643	643	643	643	643
Kleibergen-Paap Wald test: F	522	522	522	384	384	384

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Belgium, Denmark, Spain, UK, Germany, Netherlands, Italy, France, Norway and Sweden.
Years: 2005-2009

Table 7: Regression IV2

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.068			.034		
	(.065)			(.065)		
S * Mig/Tot at Mean	.261*			.299**		
	(.106)			(.104)		
S at Mean	-.102***			-.112***		
	(.012)			(.014)		
Mig/Tot at Mean+1sd		.178***			.160**	
		(.050)			(.053)	
S * Mig/Tot at Mean+1sd		.261*			.299**	
		(.106)			(.104)	
S at Mean+1sd		-.085***			-.093***	
		(.012)			(.014)	
Mig/Tot at Mean-1sd			-.041			-.092
			(.100)			(.097)
S * Mig/Tot at Mean-1sd			.261*			.299**
			(.106)			(.104)
S at Mean-1sd			-.119***			-.132***
			(.015)			(.017)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.123	.123	.123	.130	.130	.130
Observations	638	638	638	638	638	638
Kleibergen-Paap Wald test: F	348	348	348	251	251	251

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Belgium, Denmark, Spain, UK, Germany, Netherlands, Italy, France, Norway and Sweden.
Years: 2005-2009

Table 8: Regression IV3

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	-.022			-.036		
	(.058)			(.052)		
S * Mig/Tot at Mean	.410***			.464***		
	(.110)			(.109)		
S at Mean	-.093***			-.109***		
	(.010)			(.011)		
Mig/Tot at Mean+1sd		.150**			.159**	
		(.051)			(.052)	
S * Mig/Tot at Mean+1sd		.410***			.464***	
		(.110)			(.109)	
S at Mean+1sd		-.066***			-.079***	
		(.012)			(.013)	
Mig/Tot at Mean-1sd			-.194*			-.230**
			(.092)			(.083)
S * Mig/Tot at Mean-1sd			.410***			.464***
			(.110)			(.109)
S at Mean-1sd			-.120***			-.139***
			(.013)			(.014)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.125	.125	.125	.137	.137	.137
Observations	672	672	672	672	672	672
Kleibergen-Paap Wald test: F	511	511	511	37	37	37

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Denmark, Spain, United Kingdom, Italy, Norway and Sweden.
Years: 2001-2009

Table 9: Regression IV4

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.036			-.012		
	(.086)			(.069)		
S * Mig/Tot at Mean	.333**			.413***		
	(.123)			(.105)		
S at Mean	-.108***			-.127***		
	(.015)			(.016)		
Mig/Tot at Mean+1sd		.176**			.161**	
		(.063)			(.059)	
S * Mig/Tot at Mean+1sd		.333**			.413***	
		(.123)			(.105)	
S at Mean+1sd		-.086***			-.100***	
		(.016)			(.016)	
Mig/Tot at Mean-1sd			-.104			-.186
			(.128)			(.100)
S * Mig/Tot at Mean-1sd			.333**			.413***
			(.123)			(.105)
S at Mean-1sd			-.130***			-.154***
			(.018)			(.019)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.130	.130	.130	.152	.152	.152
Observations	395	395	395	395	395	395
Kleibergen-Paap Wald test: F	232	232	232	200	200	200

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Denmark, Spain, United Kingdom, Italy, Norway and Sweden.
Years: 2005-2009

Table 10: Regression IV5

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	-.095*			-.051		
	(.043)			(.046)		
S * Mig/Tot at Mean	-.037			-.100		
	(.160)			(.167)		
S at Mean	-.080***			-.092***		
	(.008)			(.009)		
Mig/Tot at Mean+1sd		-.111			-.093	
		(.059)			(.062)	
S * Mig/Tot at Mean+1sd		-.037			-.100	
		(.160)			(.167)	
S at Mean+1sd		-.083***			-.098***	
		(.016)			(.017)	
Mig/Tot at Mean-1sd			-.080			-.009
			(.096)			(.102)
S * Mig/Tot at Mean-1sd			-.037			-.100
			(.160)			(.167)
S at Mean-1sd			-.078***			-.085***
			(.011)			(.012)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.095	.095	.095	.098	.098	.098
Observations	1083	1083	1083	1083	1083	1083
Kleibergen-Paap Wald test: F	30	30	30	34	34	34

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Belgium, Denmark, Spain, UK, Germany, Netherlands, Italy, France, Norway and Sweden.
Years:2001-2009

The results confirm the positive sign of β_1 and β_3 as in the full sample, but with much greater point values pointing to the peculiarity of the two Southern European countries. In quantitative terms, when doubling the migration-to-labor force ratio the weight of simple-task sectors have increased between 0.3 and 1.3%.

Table 11: Regression OLS: Reduced Sample

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.046			.076		
	(.069)			(.074)		
S * Mig/Tot at Mean	.434***			.464***		
	(.122)			(.120)		
S at Mean	-.076***			-.087***		
	(.020)			(.019)		
Mig/Tot at Mean+1sd		.329**			.378***	
		(.103)			(.105)	
S * Mig/Tot at Mean+1sd		.434***			.464***	
		(.122)			(.120)	
S at Mean+1sd		-.029*			-.036*	
		(.014)			(.014)	
Mig/Tot at Mean-1sd			-.236*			-.226*
			(.107)			(.111)
S * Mig/Tot at Mean-1sd			.434***			.464***
			(.122)			(.120)
S at Mean-1sd			-.124***			-.138***
			(.031)			(.030)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.103	.103	.103	.072	.072	.072
Observations	196	196	196	196	196	196

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation *** p<0.01,** p<0.05, * p<0.1.
Considered countries: Spain and Italy.
Years: 2001-2009

Table 12: Regression IV1: Reduced Sample

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.235**			.219**		
	(.079)			(.081)		
S * Mig/Tot at Mean	.565***			.586***		
	(.159)			(.152)		
S at Mean	-.139***			-.144***		
	(.029)			(.027)		
Mig/Tot at Mean+1sd		.603***			.600***	
		(.131)			(.131)	
S * Mig/Tot at Mean+1sd		.565***			.586***	
		(.159)			(.152)	
S at Mean+1sd		-.077***			-.079***	
		(.017)			(.016)	
Mig/Tot at Mean-1sd			-.133			-.163
			(.129)			(.125)
S * Mig/Tot at Mean-1sd			.565***			.586***
			(.159)			(.152)
S at Mean-1sd			-.201***			-.208***
			(.045)			(.042)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.142	.142	.142	.121	.121	.121
Observations	140	140	140	140	140	140
Kleibergen-Paap Wald test: F	149	149	149	184	184	184

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Spain and Italy.
Years: 2005-2009

Table 13: Regression IV2: Reduced Sample

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.263***			.217**		
	(.077)			(.083)		
S * Mig/Tot at Mean	.570***			.592***		
	(.154)			(.145)		
S at Mean	-.144***			-.144***		
	(.028)			(.028)		
Mig/Tot at Mean+1sd		.634***			.603***	
		(.127)			(.133)	
S * Mig/Tot at Mean+1sd		.570***			.592***	
		(.154)			(.145)	
S at Mean+1sd		-.081***			-.079***	
		(.017)			(.017)	
Mig/Tot at Mean-1sd			-.108			-.169
			(.126)			(.118)
S * Mig/Tot at Mean-1sd			.570***			.592***
			(.154)			(.145)
S at Mean-1sd			-.206***			-.209***
			(.043)			(.042)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.138	.138	.138	.121	.121	.121
Observations	140	140	140	140	140	140
Kleibergen-Paap Wald test: F	169	169	169	163	163	163

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation
*** p<0.01,** p<0.05, * p<0.1.
Considered countries: Spain and Italy.
Years: 2005-2009

Table 14: Regression IV3: Reduced Sample

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.180			.117		
	(.114)			(.113)		
S * Mig/Tot at Mean	.729***			.775***		
	(.197)			(.179)		
S at Mean	-.114***			-.116***		
	(.026)			(.024)		
Mig/Tot at Mean+1sd		.655***			.621***	
		(.193)			(.186)	
S * Mig/Tot at Mean+1sd		.729***			.775***	
		(.197)			(.179)	
S at Mean+1sd		-.034			-.031	
		(.021)			(.020)	
Mig/Tot at Mean-1sd			-.295*			-.388**
			(.147)			(.135)
S * Mig/Tot at Mean-1sd			.729***			.775***
			(.197)			(.179)
S at Mean-1sd			-.194***			-.201***
			(.043)			(.039)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.057	.057	.057	.038	.038	.038
Observations	196	196	196	196	196	196
Kleibergen-Paap Wald test: F	35	35	35	46	46	46

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation *** p<0.01,** p<0.05, * p<0.1.
Considered countries: Spain and Italy.
Years: 2001-2009

Table 15: Regression IV4: Reduced Sample

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	.144			.055		
	(.102)			(.113)		
S * Mig/Tot at Mean	.566***			.602***		
	(.143)			(.130)		
S at Mean	-.125***			-.123***		
	(.029)			(.028)		
Mig/Tot at Mean+1sd		.512***			.447**	
		(.139)			(.149)	
S * Mig/Tot at Mean+1sd		.566***			.602***	
		(.143)			(.130)	
S at Mean+1sd		-.063**			-.057**	
		(.020)			(.020)	
Mig/Tot at Mean-1sd			-.225			-.337*
			(.137)			(.133)
S * Mig/Tot at Mean-1sd			.566***			.602***
			(.143)			(.130)
S at Mean-1sd			-.187***			-.189***
			(.042)			(.040)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.147	.147	.147	.123	.123	.123
Observations	140	140	140	140	140	140
Kleibergen-Paap Wald test: F	92	92	92	79	79	79

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation *** p<0.01,** p<0.05, * p<0.1.
Considered countries: Spain and Italy.
Years: 2005-2009

Table 16: Regression IV5: Reduced Sample

	1	2	3	4	5	6
Dep. Var.: $VA_s/\sum_s VA_s$	b/se	b/se	b/se	b/se	b/se	b/se
Mig/Tot at Mean	-.210			-.040		
	(.134)			(.133)		
S * Mig/Tot at Mean	.537***			.560***		
	(.152)			(.154)		
S at Mean	-.054*			-.081***		
	(.025)			(.023)		
Mig/Tot at Mean+1sd		.140			.325*	
		(.169)			(.162)	
S * Mig/Tot at Mean+1sd		.537***			.560***	
		(.152)			(.154)	
S at Mean+1sd		.005			-.019	
		(.018)			(.019)	
Mig/Tot at Mean-1sd			-.560***			-.405*
			(.165)			(.172)
S * Mig/Tot at Mean-1sd			.537***			.560***
			(.152)			(.154)
S at Mean-1sd			-.113**			-.143***
			(.039)			(.036)
Country and Time Effects	No	No	No	Yes	Yes	Yes
Adj. R^2	.049	.049	.049	.061	.061	.061
Observations	196	196	196	196	196	196
Kleibergen-Paap Wald test: F	56	56	56	98	98	98

Standard errors (in parenthesis) are robust to heteroscedasticity and arbitrary autocorrelation *** p<0.01,** p<0.05, * p<0.1.
Considered countries: Spain and Italy.
Years:2001-2009

6 Concluding Remarks

In the last ten years Europe has experienced an unprecedented increase in its immigrant population, in particular in some countries as Italy and Spain. Previous work on Europe, as D'Amuri and Peri (2014), has shown that the impact on wages is negligible, particularly on natives for whom it is even somewhat positive. Following the idea that there may be a relocation of natives in more complex-intensive occupations, while migrants take simple-task intensive occupations, the purpose of this work is to evaluate the impact of the inflow of migrants on the production structure of a selection of European countries. The hypothesis is that the inflow of migrants represents a shock in the supply of manual and physical tasks and this increase is absorbed by a relative change in the production mix with an increase in the production of sectors characterized by simple-task intensity, rather than on wages. The task complexity at the industry level is estimated using the recent dataset PIAAC (Programme for the International Assessment od Adult Competencies, OECD) that gives the advantage of country-specific parameters for the task content of the various occupations rather than using the US-based O*NET database.

Our results confirm the maintained hypothesis for the period of intense migration (2001-2009). In particular, our estimates detect relevant nonlinear effect such that the positive effect of the presence of migrants in simple-task intensive sectors is reinforced by the degree of "simplicity" of those sectors. Moreover, the effect is positive and significant in the range of high "sector simplicity" and high share of foreign born workers. In quantitative terms, on average the weight of simple-task intensive sectors increases by 0.2% when doubling the weight of migration in the active population, but when considering rapid-immigration countries, like Italy and

Spain, the increase in the weight of simple-task-intensive sectors' value added rises between 0.3 and 1.3%.

References

Accetturo, A., Bugamelli, M., and Lamorgese, A. (2012). Welcome to the machine: firms' reaction to low-skilled immigration. Temi di discussione (Economic working papers) 846, Bank of Italy, Economic Research and International Relations Area.

Altonji, J. and Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In Abowd, J. and Freeman, R., editors, *Immigration, Trade and the Labor Market*. University of Chicago Press.

Autor, D. H. and Handel, M. J. (2009). Putting Tasks to the Test: Human Capital, Job Tasks and Wages. NBER Working Papers 15116, National Bureau of Economic Research, Inc.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118:1279– 1333.

Bettin, G., Turco, A. L., and Maggioni, D. (2012). A firm-level perspective on migration. Development Working Papers 328, Centro Studi Luca d'Agliano, University of Milano.

Borelli, S. (2016). How Workers' Skills Are Used at Work: A Multi-Country Comparison with PIAAC. Working Papers 5/16, Sapienza University of Rome, DISS.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics*, 118(4):1335–1374.

Borjas, G. J. and Katz, L. F. (2007). *The Evolution of the Mexican-Born Workforce in the United States*, pages 13–56. University of Chicago Press.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics*, 19(1):22–64.

Card, D. (2007). How Immigration Affects U.S. Cities. *CReAM Discussion Paper*, (11).

Card, D. (2009). Immigration and Inequality. *American Economic Review*, 99(2):1–21.

Card, D. and Lewis, E. G. (2007). The diffusion of mexican immigrants during the 1990s: Explanations and impacts. In *Mexican Immigration to the United States*, NBER Chapters, pages 193–228. National Bureau of Economic Research, Inc.

D'Amuri, F. and Peri, G. (2014). Immigration, Jobs, And Employment Protection: Evidence From Europe Before And During The Great Recession. *Journal of the European Economic Association*, 12(2):432–464.

De Arcangelis, G., Di Porto, E., and Santoni, G. (2015). Migration, labor tasks and production structure. *Regional Science and Urban Economics*, 53(C):156–169.

Dustmann, C. and Frattini, T. (2011). Immigration: The European Experience. CReAM Discussion Paper Series 1122, Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London.

Dustmann, C. and Glitz, A. (2015). How Do Industries and Firms Respond to Changes in Local Labor Supply? *Journal of Labor Economics*, 33(3):711 – 750.

Dustmann, C., Schönberg, U., and Stuhler, J. (2016). The Impact of Immigration: Why Do Studies Reach Such Different Results? *Journal of Economic Perspectives*, 30(4):31–56.

Gandal, N., Hanson, G. H., and Slaughter, M. J. (2004). Technology, trade, and adjustment to immigration in israel. *European Economic Review*, 48(2):403–428.

Gonzalez, L. and Ortega, F. (2011). How do very open economies adjust to large immigration flows? evidence from spanish regions. *Labour Economics*, 18(1):57–70.

Goos, M. and Manning, A. (2003). Lousy and Lovely Jobs: the Rising Polarization of Work in Britain. CEP Discussion Papers dp0604, Centre for Economic Performance, LSE.

GOOS, M., Manning, A., and Salomons, A. (2011). Explaining job polarization: the roles of technology, offshoring and institutions. Center for Economic Studies - Discussion papers ces11.34, Katholieke Universiteit Leuven, Centrum voor Economische Studiën.

Hanson, G. H. and Slaughter, M. J. (2002). Labor-market adjustment in open economies: Evidence from us states. *Journal of International Economics*, 57(1):3–29.

Lewis, E. (2004). How did the Miami labor market absorb the Mariel immigrants? Technical report.

Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. *The Quarterly Journal of Economics*, 126(2):1029–1069.

Ortega, F. and Peri, G. (2014). Openness and income: The roles of trade and migration. *Journal of International Economics*, 92(2):231–251.

Ottaviano, G. I. P. and Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association*, 10(1):152–197.

Ottaviano, G. I. P., Peri, G., and Wright, G. C. (2013). Immigration, Offshoring, and American Jobs. *American Economic Review*, 103(5):1925–59.

Peri, G. (2016). Immigrants, Productivity, and Labor Markets. *Journal of Economic Perspectives*, 30(4):3–30.

Peri, G. and Sparber, C. (2009). Task specialization, immigration, and wages. *American Economic Journal: Applied Economics*, 1(3):135–69.

United Nations (2015). Trends in International Migrant Stock: Migrants by Destination and Origin (United Nations database, POP/DB/MIG/Stock/Rev. 2015). Technical report, United Nations, Department of Economic and Social Affairs, Population Division, New York.

A An example of how using PIAAC to determine industry task intensities

We consider two cases depending on whether there is industry variations in task intensities.

A.1 Case 1: no industry variation in terms of task intensities

For country I let us assume that we have the following distribution of occupations in the two industries A and B in terms of number of workers:

Table 17: Distribution of occupations by industries

	industries		
occupations	**A**	**B**	**total**
managers	10	2	12
white collars	10	18	28
blue collars	40	20	60

In O*NET there's no distinction of occupation by industry and the same aggregated data are available from PIAAC at the country level (about 4500-5000 interviews in each country). Numerical values – we have 0-4 (0 is no usage and 4 is every-day usage) in PIAAC and 1-5 in O*NET – define the intensity use of ***each task*** for ***each occupation***. Let us simplify with just two tasks, simple and complex. Then, the information from O*NET and PIAAC will be as follows:

Table 18: Numerical values (0-4) as from PIAAC (no industry variation)

	Tasks	
occupations	**complex**	**simple**
managers	3	1
white collars	2	2
blue collars	1	4

In this case the percentiles to assign to the tasks are very simple since they coincide with the distribution of occupations in the economy and are reported in Table 19.

Table 19: Mapping the PIAAC numerical values into percentiles as a measure of task intensity by occupation

	Tasks	
occupations	**complex**	**simple**
managers	0.88	0
white collars	0.6	0.12
blue collars	0	0.4

For example, let us consider complex tasks. Managers are assigned 0.88 since managers are 12 % of the total employees according to Table 17. This means that 88% of total employees are using complex tasks less intensively than the managers. White collars are an additional 28% and they use complex tasks less intensively than managers, but more intensively that blue collars. Hence, 0.6 to white collars means that 60% of the total employees (i.e. the percentage of blue collars) is using complex tasks less intensively than white collars. Blue collars use complex tasks in the relatively least way; therefore, their index is 0 since no one is using complex tasks less intensively.

From these average values it is then possible to obtain the average task intensities of each sector. For instance, the index of complex task intensity for industry A will be obtained by multiplying the task index above times the weight of each occupation in that industry:

$$0.88 \times (0.10) + 0.60 \times (0.10) = 0.148$$

For industry B:

$$0.88 \times (0.02) + 0.60 \times (0.18) = 0.1256$$

Hence, the task intensities by industry are given by the following Table 20.

Table 20: Industry task intensities without industry variation in PIAAC and O*NET

	industries	
Tasks	**A**	**B**
complex	0.148	0.1256
simple	0.252	0.1416

A.2 Case 2: industry variation in terms of task intensities

From PIAAC we have numerical values 0-4 (0 is no usage and 4 is every-day usage) that define the intensity use of ***each task*** for ***each occupation*** in ***each industry***. In Table 2 all the tasks/skills are presented, but here we simplify again by considering just two tasks, simple and complex. Hence, from PIAAC we could have a table like the following Table 21.

Table 21: Numerical values (0-4) as from PIAAC (with industry variation)

	Tasks			
	industry A		*industry B*	
occupations	**complex**	**simple**	**complex**	**simple**
managers	3	1	2	2
white collars	2	2	1	2
blue collars	1	4	1	3

Then, the index of task intensity similar to Table 19 can now be finer with data at the industry level. The task intensities at the occupational level and at the industry level are reported in Table 22.

Table 22: Mapping the PIAAC numerical values into percentiles as a measure of task intensity by occupation and by industry

	Tasks			
	industry A		*industry B*	
occupations	**complex**	**simple**	**complex**	**simple**
managers	0.90	0	0.78	0.10
white collars	0.78	0.10	0	0.10
blue collars	0	0.60	0	0.40

For example, let us consider the managers in Industry A. Table 21 shows that managers in Industry A have the highest value (i.e. 3) and no one in the economy is using complex tasks more intensively. The managers in Industry A are 10% of total employment; therefore, 90% of total employment is using complex tasks less intensively and the index to assign to managers in Industry A is 0.90. Managers in Industry B and white collars in Industry A have the same index 2 from the PIAAC survey. Since managers in Industry B are 2% and white collars in Industry A are 10%, their index is 0.78 for both since 78% of total employment is using complex tasks less intensively – or 22% (i.e. 10% of managers in Industry A, 2% managers in Industry B and 10% white collars in Industry A) are using complex tasks as intensively or more.

Then, it is possible to obtain the task intensity of each industry in a more precise way. For instance, the index of complex-task intensity of industry A is now given by:

$$0.90 \times (0.10) + 0.78 \times (0.10) = 0.168$$

Analogously for industry B:

$$0.78 \times (0.02) = 0.0156$$

Hence, Table 23.

Table 23: Industry task intensities with industry variation in PIAAC

	industries	
Tasks	**A**	**B**
complex	0.168	0.0156
simple	0.25	0.1

A possible problem with this approach is that the task intensities depend on the employment and smaller industries will show a smaller usage of all types of tasks (as in Table 23 above). Hence, what counts more is *relative* task intensity, as it has been constructed with the S index in the paper or as in Peri and Sparber (2009) and in Borelli (2016) with the TCI index – see Borelli (2016) page 25.

B Activity Sectors NACE Under Different Revisions 1.1 and 2.0

Table A1: Activity Sectors NACE rev. 1.1 (1 digit)

Agriculture, hunting and forestry	A
Fishing	B
Mining and quarrying	C
Manufacturing	D
Electricity, gas and water supply	E
Construction	F
Wholesale and retail trade; repair of motor vehicles motorcycles and personal and household goods	G
Hotels and restaurants	H
Transport, storage and communication	I
Financial intermediation	J
Real estate, renting and business activities	K
Public administration and defence; compulsory social security	L
Education	M
Health and social work	N
Other community, social and personal service activities	O
Activities of households	P
Extra-territorial organisations and bodies	Q

Table A2: Activity Sectors NACE rev. 2 (1 digit)

Agriculture, forestry and fishing	A
Mining and quarrying	B
Manufacturing	C
Electricity, gas, steam and air conditioning supply	D
Water supply; sewerage, waste management and remediation activities	E
Construction	F
Wholesale and retail trade; repair of motor vehicles and motorcycles	G
Transportation and storage	H
Accommodation and food service activities	I
Information and communication	J
Financial and insurance activities	K
Real estate activities	L
Professional, scientific and technical activities	M
Administrative and support service activities	N
Public administration and defence; compulsory social security	O
Education	P
Human health and social work activities	Q
Arts, entertainment and recreation	R
Other service activities	S
Activities of households as employers	T